# ROB521: Assignment 2

Drini Kerciku — 1004750780 March 23, 2023

#### 1 Wheel Odometry Algorithm: Noise-Free

The path estimated through dead reckoning aligns with respect to the ground truth with small shifts in various segments, more prominent when the turning rate increases significantly. Moreover, the errors in heading and position do not grow without bounds due to having the true control inputs at our disposal, and change in magnitude based on the control inputs at those particular time frames. Error values settle down to a reasonable magnitude considering that we are purely estimating with kinematic model without accounting for dynamics and other uncertainty factors such as wheel slippage.

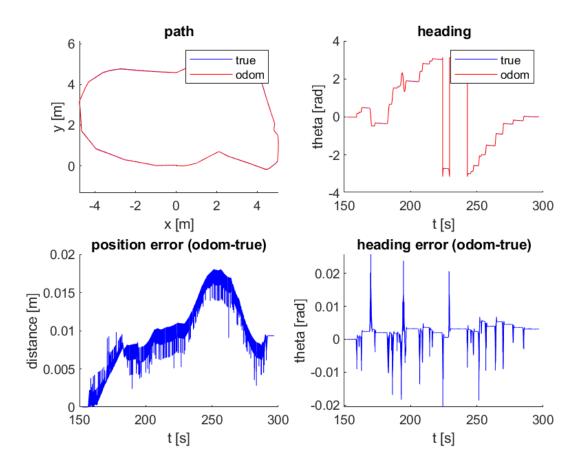


Figure 1: Dead reckoning estimation v. ground truth.

## 2 Wheel Odometry Algorithm: Noisy

A series of paths generated with noisy inputs are plotted on Figure 2, depicting how error grows in the simulation with time. Controls used for every path are susceptible to uniform noise that differs from trial to trial, implying that when the noise component is larger in magnitude, the respective path diverges by a larger magnitude and faster from the ground truth.

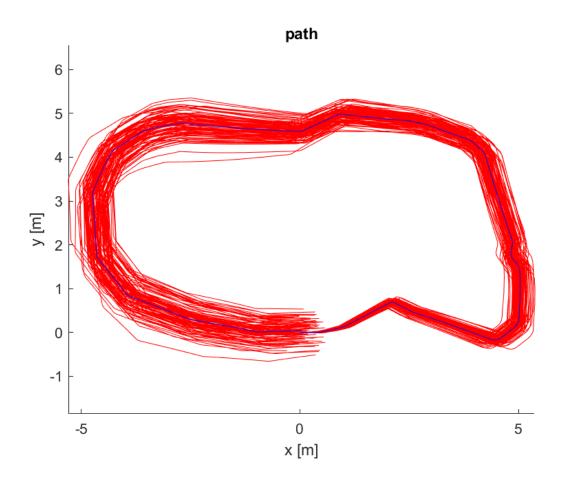


Figure 2: 100 paths generate from noise susceptible inputs v. ground truth.

### 3 Lidar Mapping

The map generated with noisy odometry data does not align properly with the ground truth. We can observe drift due to large control inputs in terms of velocity since we are not mapping when the angular rates exceed 0.1 rad/s - displaced regions due to uncertainty accumulated throughout driving and dead reckoning. Moreover, several map segments are duplicated and displaced from one another due to drift, dead reckoning accumulated error, and scanning of the same region between consecutive time stamps to another. Of course, errors due to interpolation of the noisy odometry estimations are additional factors for the observed inaccuracies between the true map and the estimated one, even though correspondence is present.

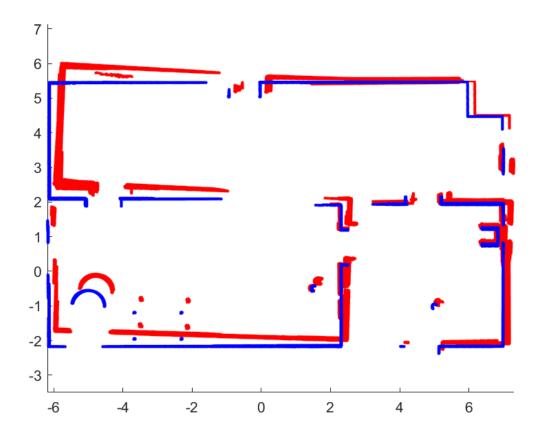


Figure 3: Mapping through Lidar with noisy input and comparison with ground truth.

#### 4 Source Code

```
1 % =====
2 % ROB521_assignment2.m
3 % =====
_{5} % This assignment will introduce you to the idea of estimating the motion
^{6} % of a mobile robot using wheel odometry, and then also using that wheel
	au % odometry to make a simple map. It uses a dataset previously gathered in
8 % a mobile robot simulation environment called Gazebo. Watch the video,
_{\rm 9} % 'gazebo.mp4' to visualize what the robot did, what its environment
10 % looks like, and what its sensor stream looks like.
11 %
12 % There are three questions to complete (5 marks each):
14 %
        Question 1: code (noise-free) wheel odometry algorithm
        Question 2: add noise to data and re-run wheel odometry algorithm
15 %
16 %
        Question 3: build a map from ground truth and noisy wheel odometry
17 %
_{18} % Fill in the required sections of this script with your code, run it to
^{19} % generate the requested plots, then paste the plots into a short report ^{20} % that includes a few comments about what you've observed. Append your
_{21} % version of this script to the report. Hand in the report as a PDF file.
22 %
23 % requires: basic Matlab, 'ROB521_assignment2_gazebo_data.mat'
25 % T D Barfoot, December 2015
26 %
27 clear all; clc;
29 % set random seed for repeatability
30 rng(1);
31
32 % ==========
33 % load the dataset from file
34 % ===============
35 %
        ground truth poses: t_true x_true y_true theta_true
36 %
37 % odometry measurements: t_odom v_odom omega_odom
38 %
               laser scans: t_laser y_laser
       laser range limits: r_min_laser r_max_laser
39 %
       laser angle limits: phi_min_laser phi_max_laser
41 %
42 load ROB521_assignment2_gazebo_data.mat;
43
44 % =======
45 % Question 1: code (noise-free) wheel odometry algorithm
47 %
^{48} % Write an algorithm to estimate the pose of the robot throughout motion
49 % using the wheel odometry data (t_odom, v_odom, omega_odom) and assuming
_{50} % a differential-drive robot model. Save your estimate in the variables
\% (x_odom y_odom theta_odom) so that the comparison plots can be generated \% below. See the plot 'ass1_q1_soln.png' for what your results should look
53 % like.
54
55 % variables to store wheel odometry pose estimates
56 numodom = size(t_odom,1);
x_odom = zeros(numodom,1);
58 y_odom = zeros(numodom,1);
59 theta_odom = zeros(numodom,1);
61 % set the initial wheel odometry pose to ground truth
x_{odom}(1) = x_{true}(1);
63 y_odom(1) = y_true(1);
64 theta_odom(1) = theta_true(1);
66 q_i = [x_odom(1); y_odom(1); theta_odom(1)];
67 t_i = t_true(1);
_{\rm 69} % -----insert your wheel odometry algorithm here-----
70 for i=2:numodom
```

```
\mbox{\%} obtain control inputs and dt between time stamps
 72
 73
        currU = [v_odom(i - 1); omega_odom(i - 1)];
        dt = t_true(i) - t_i;
 74
 75
        % generate matric G(q)
 76
        G_q = [\cos(q_i(3)) \ 0; \sin(q_i(3)) \ 0; \ 0 \ 1];
 77
        q_i = q_i + dt*G_q*currU;
 78
 79
        % make sure that theta remains in the range [-pi, pi]
 80
 81
        if (q_i(3) > 0) && (q_i(3) > pi)
 82
            q_i(3) = q_i(3) - 2*pi;
 83
        elseif (q_i(3) < 0) \&\& (q_i(3) < -pi)
 85
 86
            q_i(3) = q_i(3) + 2*p_i;
 87
 88
 89
        end
 90
       % prepare for next iteration
 91
 92
        t_i = t_true(i);
       x_{odom(i)} = q_{i(1)};
 93
        y_{odom(i)} = q_{i}(2);
 94
        theta_odom(i) = q_i(3);
 96
 97 end
98 % ----end of your wheel odometry algorithm-----
_{100} % plot the results for verification
101 figure(1)
102 clf;
103
104 subplot (2,2,1);
105 hold on;
plot(x_true,y_true,'b');
plot(x_odom, y_odom, 'r');

108 legend('true', 'odom');

109 xlabel('x [m]');
110 ylabel('y [m]');
title('path');
112 axis equal;
113
subplot(2,2,2);
115 hold on:
plot(t_true, theta_true, 'b');
plot(t_odom,theta_odom,'r');
legend('true', 'odom');
119 xlabel('t [s]');
ylabel('theta [rad]');
title('heading');
122
subplot(2,2,3);
124 hold on;
pos_err = zeros(numodom,1);
126 for i=1:numodom
       pos\_err(i) = sqrt((x\_odom(i)-x\_true(i))^2 + (y\_odom(i)-y\_true(i))^2);
127
128 end
plot(t_odom,pos_err,'b');
130 xlabel('t [s]');
ylabel('distance [m]');
132 title('position error (odom-true)');
133
134 subplot(2,2,4);
135 hold on;
theta_err = zeros(numodom,1);
137 for i=1:numodom
138
       phi = theta_odom(i) - theta_true(i);
        while phi > pi
139
140
           phi = phi - 2*pi;
141
       while phi < -pi
142
          phi = phi + 2*pi;
144 end
```

```
theta_err(i) = phi;
146 end
plot(t_odom, theta_err, 'b');
148 xlabel('t [s]');
ylabel('theta [rad]');
title('heading error (odom-true)');
print -dpng ass1_q1.png
155 % Question 2: add noise to data and re-run wheel odometry algorithm
156 % =
157 %
_{\rm 158} % Now we're going to deliberately add some noise to the linear and
_{159} % angular velocities to simulate what real wheel odometry is like. Copy
_{160} % your wheel odometry algorithm from above into the indicated place below
_{161} % to see what this does. The below loops 100 times with different random _{162} % noise. See the plot 'ass1_q2_soln.pdf' for what your results should look
163 % like.
164
165 % save the original odometry variables for later use
v_odom_noisefree = v_odom;
omega_odom_noisefree = omega_odom;
169 % set up plot
170 figure (2);
171 clf;
172 hold on;
173
174 % loop over random trials
175 for n=1:100
176
       \% add noise to wheel odometry measurements (yes, on purpose to see effect)
       v_odom = v_odom_noisefree + 0.2*randn(numodom,1);
178
       omega_odom = omega_odom_noisefree + 0.04*randn(numodom,1);
179
180
       q_i = [x_odom(1); y_odom(1); theta_odom(1)];
181
182
       t_i = t_true(1);
183
184
       \% -----insert your wheel odometry algorithm here-----
       for i=2:numodom
185
186
       % obtain control inputs and dt between time stamps
187
       currU = [v_odom(i - 1); omega_odom(i - 1)];
188
       dt = t_true(i) - t_i;
189
190
       191
       G_q = [\cos(q_i(3)) \ 0; \sin(q_i(3)) \ 0; \ 0 \ 1];
192
       q_i = q_i + dt*G_q*currU;
193
194
       % make sure that theta remains in the range [-pi, pi]
195
       if (q_i(3) > 0) && (q_i(3) > pi)
196
197
           q_i(3) = q_i(3) - 2*pi;
198
199
       elseif (q_i(3) < 0) & (q_i(3) < -pi)
200
201
           q_i(3) = q_i(3) + 2*pi;
202
203
       end
204
205
       % prepare for next iteration
206
       t_i = t_true(i);
207
       x_{odom(i)} = q_{i(1)};
       y_{odom(i)} = q_{i(2)};
209
       theta_odom(i) = q_i(3);
210
211
212
213
       % -----end of your wheel odometry algorithm-----
214
       % add the results to the plot
215
       plot(x_odom, y_odom, 'r');
216
217 end
```

```
218
219 % plot ground truth on top and label
plot(x_true,y_true,'b');
221 xlabel('x [m]');
222 ylabel('y [m]');
title('path');
224 axis equal;
225 print -dpng ass1_q2.png
226
227
229 % Question 3: build a map from noisy and noise-free wheel odometry
231 %
_{232} % Now we're going to try to plot all the points from our laser scans in the
_{233} % robot's initial reference frame. This will involve first figuring out
_{\rm 234} % how to plot the points in the current frame, then transforming them back
^{235} % to the initial frame and plotting them. Do this for both the ground
236 % truth pose (blue) and also the last noisy odometry that you calculated in
^{237} % Question 2 (red). At first even the map based on the ground truth may ^{238} % not look too good. This is because the laser timestamps and odometry
^{239} % timestamps do not line up perfectly and you'll need to interpolate. Even
_{240} % after this, two additional patches will make your map based on ground
_{241} % truth look as crisp as the one in 'ass1_q3_soln.png'. The first patch is
_{242} % to only plot the laser scans if the angular velocity is less than
^{243} % 0.1 rad/s; this is because the timestamp interpolation errors have more
^{244} % of an effect when the robot is turning quickly. The second patch is to
_{245} % account for the fact that the origin of the laser scans is about 10 cm
_{246} % behind the origin of the robot. Once your ground truth map looks crisp,
^{247} % compare it to the one based on the odometry poses, which should be far
_{\rm 248} % less crisp, even with the two patches applied.
250 % set up plot
251 figure(3);
252 clf;
253 hold on:
255 % precalculate some quantities
points = size(y_laser,2);
angles = linspace(phi_min_laser, phi_max_laser,npoints);
258 cos_angles = cos(angles);
sin_angles = sin(angles);
260
261 for n=1:2
262
       if n==1
263
           \% interpolate the noisy odometry at the laser timestamps
264
           t_interp = linspace(t_odom(1),t_odom(numodom),numodom);
           x_interp = interp1(t_interp,x_odom,t_laser);
266
            y_interp = interp1(t_interp,y_odom,t_laser);
267
            theta_interp = interp1(t_interp,theta_odom,t_laser);
268
           omega_interp = interp1(t_interp,omega_odom,t_laser);
269
270
            colour = 'r.';
271
272
           \mbox{\ensuremath{\mbox{\%}}} interpolate the noise-free odometry at the laser timestamps
           t_interp = linspace(t_true(1),t_true(numodom),numodom);
273
            x_interp = interp1(t_interp,x_true,t_laser);
274
            y_interp = interp1(t_interp,y_true,t_laser);
275
276
            theta_interp = interp1(t_interp,theta_true,t_laser);
            omega_interp = interp1(t_interp,omega_odom,t_laser);
277
            colour = 'b.';
278
279
280
       % loop over laser scans
281
       for i=1:size(t_laser,1)
282
283
284
            % -----insert your point transformation algorithm here-----
285
            if abs(omega_interp(i)) < 0.1</pre>
286
                % extract data from the i-th reading
287
                Rlaser_i = y_laser(i,:);
288
                % transform in x,y coordinates in robots local frame
                QLaser_i = [Rlaser_i.*cos_angles; Rlaser_i.*sin_angles];
290
```

```
291
                 \% generate rotation matrix from local to global frame
292
                 293
294
                 % map to the gloabl reference frame
QGlobal = R_i*(QLaser_i - [0.1; 0]) + [x_interp(i); y_interp(i)];
plot(QGlobal(1,:), QGlobal(2,:), colour)
296
297
298
299
300
            \% -----end of your point transformation algorithm-----
301
302
303 end
304
axis equal;
print -dpng ass1_q3.png
```